Clasificación Binaria

Estudiantes de Portugués

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Carga de los datos y librerías

```r
students.csv <- file.path(getwd(), 'student-por.csv')
STUDENTS <- read.csv2(file = students.csv, header = TRUE, sep = ';')

summary(STUDENTS)
```

```
##  school   sex          age        address famsize   Pstatus
##  GP:423   F:292   Min.   :15.00   R:127   GT3:358   A: 61
##  MS: 76   M:207   1st Qu.:16.00   U:372   LE3:141   T:438
##                   Median :16.00
##                   Mean   :16.58
##                   3rd Qu.:17.00
##                   Max.   :22.00
##       Medu            Fedu              Mjob           Fjob
##  Min.   :0.000   Min.   :0.000   at_home : 93   at_home : 23
##  1st Qu.:2.000   1st Qu.:1.000   health  : 41   health  : 19
##  Median :3.000   Median :2.000   other   :198   other   :293
##  Mean   :2.591   Mean   :2.385   services:108   services:132
##  3rd Qu.:4.000   3rd Qu.:3.000   teacher : 59   teacher : 32
##  Max.   :4.000   Max.   :4.000
##         reason      guardian     traveltime      studytime
##  course    :209   father:117   Min.   :1.000   Min.   :1.000
##  home      :128   mother:351   1st Qu.:1.000   1st Qu.:1.000
##  other     : 38   other : 31   Median :1.000   Median :2.000
##  reputation:124                Mean   :1.493   Mean   :1.976
##                                3rd Qu.:2.000   3rd Qu.:2.000
##                                Max.   :4.000   Max.   :4.000
##     failures       schoolsup famsup     paid     activities nursery
##  Min.   :0.0000   no :438   no :178   no :470   no :246    no : 99
##  1st Qu.:0.0000   yes: 61   yes:321   yes: 29   yes:253    yes:400
##  Median :0.0000
##  Mean   :0.1864
##  3rd Qu.:0.0000
##  Max.   :3.0000
##  higher    internet  romantic      famrel         freetime
##  no : 49   no :103   no :327   Min.   :1.00   Min.   :1.000
##  yes:450   yes:396   yes:172   1st Qu.:4.00   1st Qu.:3.000
##                                Median :4.00   Median :3.000
##                                Mean   :3.94   Mean   :3.198
```

```
##                                3rd Qu.:5.00   3rd Qu.:4.000  
##                                Max.   :5.00   Max.   :5.000  
##      goout            Dalc            Walc           health     
##  Min.   :1.000   Min.   :1.000   Min.   :1.000   Min.   :1.000  
##  1st Qu.:2.000   1st Qu.:1.000   1st Qu.:1.000   1st Qu.:2.000  
##  Median :3.000   Median :1.000   Median :2.000   Median :4.000  
##  Mean   :3.158   Mean   :1.483   Mean   :2.251   Mean   :3.551  
##  3rd Qu.:4.000   3rd Qu.:2.000   3rd Qu.:3.000   3rd Qu.:5.000  
##  Max.   :5.000   Max.   :5.000   Max.   :5.000   Max.   :5.000  
##     absences            G1              G2              G3       
##  Min.   : 0.000   Min.   : 0.00   Min.   : 0.00   Min.   : 0.00  
##  1st Qu.: 0.000   1st Qu.:10.00   1st Qu.:10.00   1st Qu.:11.00  
##  Median : 2.000   Median :12.00   Median :12.00   Median :12.00  
##  Mean   : 3.948   Mean   :11.74   Mean   :11.89   Mean   :12.33  
##  3rd Qu.: 6.000   3rd Qu.:13.50   3rd Qu.:13.00   3rd Qu.:14.00  
##  Max.   :32.000   Max.   :18.00   Max.   :19.00   Max.   :19.00
```

SELECCIÓN DE VARIABLES

El objetivo de este apartado es obtener las mejores variables que nos permitan optimizar nuestro modelos. El trabajo lo realizaremos en dos fases, una fase inicial en la que vamos a realizar una limpieza de datos para obtener un dataset con el que podamos generar un modelo y en segundo lugar lo que realizaremos selección de las mejores variables para optimizar nuestro modelo.

LIMPIEZA DE NA

No realizamos supresión de NA dado que no hay ninguno en el fichero.

```
check.na(STUDENTS)
```

```
## 
## There is a total of  0  NAs on this file
```

```
## [1] 0
```

Para comenzar a trabajar con las variables vamos a hacer una selección en función del tipo de variable que es, a continuación trabajaremos con las variables de forma diferente en función de la clase de variable que sea.

Lo primero que haremos será la selección de la variable objetivo (higher) y la separamos del dataset. A continuación, haremos una subdivisión de las columnas restantes entre continuas y categóricas almacenando los nombres de las columnas en dos variables.

```
vardep <- "higher"
students.bis <- STUDENTS[,-which(names(STUDENTS) == vardep)]

continuas <- names(select_if(students.bis, is.integer))
categoricas <- names(select_if(students.bis, is.factor))


cat("Nuestra variable objetivo será: ",vardep, "\n\nVariables continuas: ",continuas, "\n\nVariables ca
```

```
## Nuestra variable objetivo será:  higher
## 
## Variables continuas:  age Medu Fedu traveltime studytime failures famrel freetime goout Dalc Walc hea
## 
## Variables categoricas:  school sex address famsize Pstatus Mjob Fjob reason guardian schoolsup famsu
```

CREACIÓN DE VARIABLES DUMMY

Generamos variables dummy a partir de nuestras variables categóricas. En nuestro caso lo realizamos de todas dado que las variables categóricas no contienen un número demasiado elevado de valores diferentes.

```
## Warning in model.matrix.default(~x - 1, model.frame(~x - 1), contrasts =
## FALSE): non-list contrasts argument ignored

## Warning in model.matrix.default(~x - 1, model.frame(~x - 1), contrasts =
## FALSE): non-list contrasts argument ignored

## Warning in model.matrix.default(~x - 1, model.frame(~x - 1), contrasts =
## FALSE): non-list contrasts argument ignored

## Warning in model.matrix.default(~x - 1, model.frame(~x - 1), contrasts =
## FALSE): non-list contrasts argument ignored

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## FALSE): non-list contrasts argument ignored

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## FALSE): non-list contrasts argument ignored

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## FALSE): non-list contrasts argument ignored

## Warning in model.matrix.default(~x - 1, model.frame(~x - 1), contrasts =
## FALSE): non-list contrasts argument ignored

## Warning in model.matrix.default(~x - 1, model.frame(~x - 1), contrasts =
## FALSE): non-list contrasts argument ignored
```

ESTANDARIZACIÓN DE VARIABLES

A continuación estandarizamos las variables continuas. Para ello realizamos la media y desviación típica de las contínuas y a continuación las estandarizamos. Para trabajar ahora con todas las variables como continuas, las uno a las variables dummy generadas en el paso anterior.

```
means <- apply(students.df[,continuas],2,mean)
sds <- sapply(students.df[,continuas],sd)


students.df.bis <- scale(students.df[,continuas], center = means, scale = sds)
numerocont <- which(colnames(students.df) %in% continuas)
students.df.s <- cbind(students.df.bis, students.df[,-numerocont])
```

SELECCIÓN DE VARIABLES

El primer paso en la selección de las variables es suprimir de las variables dummy una variable, dado que esta puede ser obtenida como una negación del resto de las variables.

```
continuas <- c("age", "Medu", "Fedu", "traveltime", "studytime", "failures",
"famrel", "freetime", "goout", "Dalc", "Walc", "health", "absences",
"G1", "G2", "G3", "school.GP", "sex.M",
"address.R", "famsize.GT3", "Pstatus.A",
"Mjob.health", "Mjob.other", "Mjob.services",
"Mjob.teacher", "Fjob.health", "Fjob.other",
"Fjob.services", "Fjob.teacher", "reason.course", "reason.home",
"reason.reputation", "guardian.father", "guardian.mother",
"schoolsup.yes",
"famsup.yes", "paid.yes", "activities.yes",
"nursery.yes", "higher", "internet.yes",
"romantic.yes")

categoricas <- c("")


numerocont <- which(colnames(students.df.s) %in% continuas)
students.df.s <- students.df.s[,numerocont]


students.df.s$higher<-ifelse(students.df.s$higher=="yes","Yes","No") # Corrección de los datos para que

cat("Variables continuas: ",continuas, "\n\nVariables categoricas: ",categoricas)
```

```
## Variables continuas:  age Medu Fedu traveltime studytime failures famrel freetime goout Dalc Walc hea
##
## Variables categoricas:
```

SELECCIÓN DE VARIABLES EN CLASIFICACIÓN BINARIA LOGÍSTICA

Para la selección de variables hacemos la búsqueda mediante el uso de la medida de ajuste AIC. Para ejecutar los algoritmos lo realizaremos mediante el método stepwise que que va incluyendo y sacando variables con el objetivo de optimizar la selección.

```
full<-glm(factor(higher)~., data=students.df.s, family = binomial(link="logit"))
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
null<-glm(factor(higher)~1, data=students.df.s, family = binomial(link="logit"))
```

```r
seleccion<-stepAIC(null,scope=list(upper=full),direction="both")
```

```
## Start:  AIC=322.46
## factor(higher) ~ 1
##
##                      Df Deviance    AIC
## + G1                  1   244.03 248.03
## + G2                  1   245.51 249.51
## + G3                  1   250.65 254.65
## + failures            1   288.99 292.99
## + age                 1   291.47 295.47
## + studytime           1   296.98 300.98
## + Fedu                1   298.36 302.36
## + Medu                1   298.68 302.68
## + school.GP           1   307.53 311.53
## + absences            1   309.76 313.76
## + Mjob.health         1   311.59 315.59
## + famsup.yes          1   311.92 315.92
## + Mjob.teacher        1   313.40 317.40
## + romantic.yes        1   315.61 319.61
## + schoolsup.yes       1   316.19 320.19
## + Dalc                1   316.33 320.33
## + Fjob.health         1   316.45 320.45
## + traveltime          1   316.82 320.82
## + reason.reputation   1   316.85 320.85
## + nursery.yes         1   316.87 320.87
## + address.R           1   317.06 321.06
## + famrel              1   317.96 321.96
## + freetime            1   318.04 322.04
## + Fjob.teacher        1   318.20 322.20
## + activities.yes      1   318.33 322.33
## <none>                    320.46 322.46
## + internet.yes        1   318.52 322.52
## + reason.course       1   318.62 322.62
## + goout               1   318.66 322.66
## + guardian.father     1   318.81 322.81
## + Mjob.other          1   319.28 323.28
## + Walc                1   319.46 323.46
## + Fjob.other          1   319.47 323.47
## + guardian.mother     1   319.82 323.82
## + health              1   320.06 324.06
## + Mjob.services       1   320.10 324.10
## + paid.yes            1   320.13 324.13
## + reason.home         1   320.16 324.16
## + sex.M               1   320.20 324.20
## + Pstatus.A           1   320.25 324.25
## + famsize.GT3         1   320.31 324.31
## + Fjob.services       1   320.35 324.35
##
## Step:  AIC=248.03
## factor(higher) ~ G1
##
##                      Df Deviance    AIC
## + age                 1   228.24 234.24
```

```
## + schoolsup.yes      1   232.26 238.26
## + studytime          1   234.02 240.02
## + Fedu               1   234.86 240.86
## + G3                 1   234.90 240.90
## + Medu               1   235.55 241.55
## + G2                 1   235.95 241.95
## + Mjob.health        1   237.72 243.72
## + failures           1   237.92 243.92
## + famsup.yes         1   239.15 245.15
## + absences           1   239.62 245.62
## + romantic.yes       1   241.01 247.01
## + Fjob.health        1   241.33 247.33
## + famrel             1   241.66 247.66
## + Mjob.teacher       1   241.78 247.78
## + Fjob.teacher       1   241.93 247.93
## <none>                   244.03 248.03
## + nursery.yes        1   242.20 248.20
## + paid.yes           1   242.35 248.35
## + school.GP          1   242.53 248.53
## + Fjob.other         1   242.85 248.85
## + guardian.father    1   243.09 249.09
## + Fjob.services      1   243.19 249.19
## + reason.reputation  1   243.30 249.30
## + freetime           1   243.30 249.30
## + traveltime         1   243.63 249.63
## + Dalc               1   243.64 249.64
## + guardian.mother    1   243.68 249.68
## + health             1   243.78 249.78
## + Mjob.other         1   243.82 249.82
## + Pstatus.A          1   243.83 249.83
## + sex.M              1   243.86 249.86
## + famsize.GT3        1   243.87 249.87
## + address.R          1   243.88 249.88
## + activities.yes     1   243.94 249.94
## + reason.course      1   243.98 249.98
## + goout              1   244.00 250.00
## + internet.yes       1   244.02 250.02
## + reason.home        1   244.03 250.03
## + Mjob.services      1   244.03 250.03
## + Walc               1   244.03 250.03
## - G1                 1   320.46 322.46
##
## Step:  AIC=234.24
## factor(higher) ~ G1 + age
##
##                     Df Deviance    AIC
## + studytime          1   214.84 222.84
## + G3                 1   216.14 224.14
## + G2                 1   217.08 225.08
## + Medu               1   218.98 226.98
## + schoolsup.yes      1   219.62 227.62
## + Fedu               1   220.52 228.52
## + school.GP          1   222.08 230.08
## + Mjob.health        1   223.78 231.78
```

```
## + famsup.yes         1   224.56 232.56
## + famrel             1   225.85 233.85
## + Mjob.teacher       1   226.20 234.20
## <none>                   228.24 234.24
## + paid.yes           1   226.25 234.25
## + reason.reputation  1   226.27 234.27
## + failures           1   226.38 234.38
## + Fjob.teacher       1   226.47 234.47
## + Fjob.health        1   226.51 234.51
## + freetime           1   226.56 234.56
## + absences           1   226.58 234.58
## + nursery.yes        1   226.79 234.79
## + traveltime         1   227.32 235.32
## + romantic.yes       1   227.34 235.34
## + Fjob.other         1   227.52 235.52
## + address.R          1   227.54 235.54
## + health             1   227.58 235.58
## + Fjob.services      1   227.63 235.63
## + Pstatus.A          1   227.82 235.82
## + internet.yes       1   227.88 235.88
## + famsize.GT3        1   228.01 236.01
## + activities.yes     1   228.11 236.11
## + guardian.father    1   228.14 236.14
## + reason.course      1   228.16 236.16
## + reason.home        1   228.20 236.20
## + Mjob.other         1   228.20 236.20
## + sex.M              1   228.22 236.22
## + Mjob.services      1   228.23 236.23
## + goout              1   228.23 236.23
## + Dalc               1   228.24 236.24
## + guardian.mother    1   228.24 236.24
## + Walc               1   228.24 236.24
## - age                1   244.03 248.03
## - G1                 1   291.47 295.47
##
## Step:  AIC=222.84
## factor(higher) ~ G1 + age + studytime
##
##                     Df Deviance    AIC
## + G3                 1   205.00 215.00
## + G2                 1   205.56 215.56
## + Medu               1   206.22 216.22
## + Fedu               1   207.45 217.45
## + schoolsup.yes      1   207.84 217.84
## + school.GP          1   207.87 217.87
## + Mjob.health        1   210.30 220.30
## + famrel             1   212.00 222.00
## + Mjob.teacher       1   212.02 222.02
## + famsup.yes         1   212.15 222.15
## <none>                   214.84 222.84
## + Fjob.teacher       1   212.91 222.91
## + romantic.yes       1   213.01 223.01
## + paid.yes           1   213.52 223.52
## + freetime           1   213.53 223.53
```

```
## + Fjob.health        1   213.60 223.60
## + address.R          1   213.61 223.61
## + nursery.yes        1   213.71 223.71
## + failures           1   213.76 223.76
## + health             1   213.94 223.94
## + internet.yes       1   213.96 223.96
## + absences           1   213.96 223.96
## + sex.M              1   213.98 223.98
## + reason.reputation  1   214.17 224.17
## + Fjob.other         1   214.19 224.19
## + Pstatus.A          1   214.21 224.21
## + traveltime         1   214.27 224.27
## + Walc               1   214.38 224.38
## + Fjob.services      1   214.49 224.49
## + Dalc               1   214.53 224.53
## + famsize.GT3        1   214.60 224.60
## + goout              1   214.70 224.70
## + reason.course      1   214.75 224.75
## + guardian.father    1   214.77 224.77
## + Mjob.other         1   214.81 224.81
## + guardian.mother    1   214.82 224.82
## + reason.home        1   214.83 224.83
## + Mjob.services      1   214.83 224.83
## + activities.yes     1   214.83 224.83
## - studytime          1   228.24 234.24
## - age                1   234.02 240.02
## - G1                 1   263.36 269.36
##
## Step:  AIC=215
## factor(higher) ~ G1 + age + studytime + G3
##
##                     Df Deviance    AIC
## + school.GP          1   197.60 209.60
## + Medu               1   197.88 209.88
## + Fedu               1   199.03 211.03
## + schoolsup.yes      1   199.44 211.44
## + Mjob.health        1   201.00 213.00
## + famrel             1   201.54 213.54
## + famsup.yes         1   201.57 213.57
## + Mjob.teacher       1   202.45 214.45
## + sex.M              1   202.66 214.66
## + health             1   202.81 214.81
## <none>                   205.00 215.00
## + Walc               1   203.16 215.16
## + address.R          1   203.22 215.22
## + nursery.yes        1   203.40 215.40
## + G2                 1   203.48 215.48
## + Fjob.other         1   203.71 215.71
## + Dalc               1   203.75 215.75
## + Fjob.health        1   203.75 215.75
## + Fjob.services      1   203.75 215.75
## + Fjob.teacher       1   203.79 215.79
## + goout              1   203.86 215.86
## + paid.yes           1   203.91 215.91
```

```
## + traveltime         1   203.98 215.98
## + internet.yes       1   204.01 216.01
## + romantic.yes       1   204.13 216.13
## + Pstatus.A          1   204.17 216.17
## + absences           1   204.48 216.48
## + freetime           1   204.53 216.53
## + reason.reputation  1   204.74 216.74
## + famsize.GT3        1   204.75 216.75
## + failures           1   204.87 216.87
## + guardian.mother    1   204.91 216.91
## + guardian.father    1   204.97 216.97
## + Mjob.services      1   204.97 216.97
## + reason.home        1   204.98 216.98
## + reason.course      1   204.99 216.99
## + activities.yes     1   205.00 217.00
## + Mjob.other         1   205.00 217.00
## - G1                 1   213.62 221.62
## - G3                 1   214.84 222.84
## - studytime          1   216.14 224.14
## - age                1   226.35 234.35
##
## Step:  AIC=209.6
## factor(higher) ~ G1 + age + studytime + G3 + school.GP
##
##                     Df Deviance    AIC
## + famsup.yes         1   193.27 207.27
## + Mjob.health        1   193.88 207.88
## + Medu               1   193.93 207.93
## + schoolsup.yes      1   194.14 208.14
## + Fedu               1   194.24 208.24
## + famrel             1   194.94 208.94
## <none>                   197.60 209.60
## + nursery.yes        1   195.80 209.80
## + Mjob.teacher       1   195.94 209.94
## + Walc               1   196.03 210.03
## + Dalc               1   196.06 210.06
## + absences           1   196.09 210.09
## + health             1   196.20 210.20
## + goout              1   196.28 210.28
## + G2                 1   196.30 210.30
## + Pstatus.A          1   196.47 210.47
## + Fjob.other         1   196.50 210.50
## + Fjob.health        1   196.52 210.52
## + Fjob.services      1   196.61 210.61
## + traveltime         1   196.64 210.64
## + paid.yes           1   196.76 210.76
## + sex.M              1   196.99 210.99
## + romantic.yes       1   197.13 211.13
## + Fjob.teacher       1   197.16 211.16
## + famsize.GT3        1   197.24 211.24
## + address.R          1   197.25 211.25
## + failures           1   197.40 211.40
## + Mjob.services      1   197.43 211.43
## + internet.yes       1   197.44 211.44
```

```
## + freetime           1   197.45 211.45
## + guardian.father    1   197.47 211.47
## + reason.reputation  1   197.57 211.57
## + Mjob.other         1   197.59 211.59
## + guardian.mother    1   197.60 211.60
## + reason.course      1   197.60 211.60
## + reason.home        1   197.60 211.60
## + activities.yes     1   197.60 211.60
## - G1                 1   202.52 212.52
## - school.GP          1   205.00 215.00
## - G3                 1   207.87 217.87
## - studytime          1   209.46 219.46
## - age                1   224.55 234.55
##
## Step:  AIC=207.27
## factor(higher) ~ G1 + age + studytime + G3 + school.GP + famsup.yes
##
##                     Df Deviance    AIC
## + Mjob.health        1   189.59 205.59
## + schoolsup.yes      1   190.29 206.29
## + Medu               1   190.47 206.47
## + Fedu               1   190.62 206.62
## + Walc               1   191.03 207.03
## + famrel             1   191.04 207.04
## + G2                 1   191.16 207.16
## <none>                   193.27 207.27
## + absences           1   191.38 207.38
## + nursery.yes        1   191.38 207.38
## + health             1   191.51 207.51
## + Dalc               1   191.55 207.55
## + Mjob.teacher       1   191.83 207.83
## + sex.M              1   191.97 207.97
## + goout              1   192.02 208.02
## + Pstatus.A          1   192.09 208.09
## + Fjob.health        1   192.12 208.12
## + Fjob.services      1   192.26 208.26
## + Fjob.other         1   192.31 208.31
## + traveltime         1   192.45 208.45
## + paid.yes           1   192.52 208.52
## + romantic.yes       1   192.61 208.61
## + failures           1   192.71 208.71
## + Mjob.services      1   192.78 208.78
## + famsize.GT3        1   192.82 208.82
## - G1                 1   196.84 208.84
## + Fjob.teacher       1   192.98 208.98
## + address.R          1   192.99 208.99
## + freetime           1   193.08 209.08
## + guardian.father    1   193.09 209.09
## + reason.reputation  1   193.22 209.22
## + Mjob.other         1   193.23 209.23
## + guardian.mother    1   193.23 209.23
## + activities.yes     1   193.27 209.27
## + reason.course      1   193.27 209.27
## + internet.yes       1   193.27 209.27
```

```
## + reason.home        1   193.27 209.27
## - famsup.yes         1   197.60 209.60
## - school.GP          1   201.57 213.57
## - studytime          1   204.14 216.14
## - G3                 1   204.51 216.51
## - age                1   219.48 231.48
##
## Step:  AIC=205.59
## factor(higher) ~ G1 + age + studytime + G3 + school.GP + famsup.yes +
##     Mjob.health
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
##                     Df Deviance    AIC
## + schoolsup.yes      1   186.22 204.22
## + Fedu               1   186.85 204.85
## + Walc               1   187.25 205.25
## + Medu               1   187.31 205.31
## + famrel             1   187.39 205.39
## + nursery.yes        1   187.48 205.48
## + G2                 1   187.58 205.58
## <none>                   189.59 205.59
## + health             1   187.62 205.62
## + Dalc               1   187.74 205.74
## + absences           1   187.88 205.88
## + Mjob.teacher       1   187.95 205.95
## + Pstatus.A          1   188.02 206.02
## + goout              1   188.53 206.53
## + sex.M              1   188.60 206.60
## + Fjob.services      1   188.63 206.63
## + Fjob.other         1   188.67 206.67
## + Fjob.health        1   188.70 206.70
## + paid.yes           1   188.75 206.75
## + romantic.yes       1   188.86 206.86
## + traveltime         1   188.88 206.88
## + famsize.GT3        1   188.93 206.93
## + failures           1   189.00 207.00
## - G1                 1   193.13 207.13
## + Fjob.teacher       1   189.21 207.21
## - Mjob.health        1   193.27 207.27
## + Mjob.services      1   189.28 207.28
## + Mjob.other         1   189.34 207.34
## + address.R          1   189.36 207.36
## + freetime           1   189.38 207.38
## + guardian.father    1   189.44 207.44
## + guardian.mother    1   189.54 207.54
## + reason.home        1   189.56 207.56
## + reason.reputation  1   189.57 207.57
## + reason.course      1   189.58 207.58
## + activities.yes     1   189.59 207.59
## + internet.yes       1   189.59 207.59
## - famsup.yes         1   193.88 207.88
## - school.GP          1   197.66 211.66
## - G3                 1   200.29 214.29
## - studytime          1   200.31 214.31
```

```
## - age                1   212.87 226.87
##
## Step:  AIC=204.22
## factor(higher) ~ G1 + age + studytime + G3 + school.GP + famsup.yes +
##     Mjob.health + schoolsup.yes
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
##                     Df Deviance    AIC
## + Walc               1   183.24 203.24
## + Fedu               1   183.40 203.40
## + Medu               1   183.98 203.98
## + famrel             1   184.12 204.12
## + health             1   184.12 204.12
## <none>                   186.22 204.22
## + Mjob.teacher       1   184.22 204.22
## + nursery.yes        1   184.40 204.40
## + Dalc               1   184.50 204.50
## + G2                 1   184.57 204.57
## + Pstatus.A          1   184.58 204.58
## + goout              1   184.77 204.77
## + sex.M              1   184.89 204.89
## + absences           1   185.02 205.02
## + Fjob.services      1   185.17 205.17
## + paid.yes           1   185.18 205.18
## + Fjob.health        1   185.22 205.22
## + failures           1   185.28 205.28
## + Fjob.other         1   185.34 205.34
## - schoolsup.yes      1   189.59 205.59
## + traveltime         1   185.61 205.61
## + romantic.yes       1   185.62 205.62
## + Mjob.services      1   185.75 205.75
## + Mjob.other         1   185.81 205.81
## + freetime           1   185.85 205.85
## + famsize.GT3        1   185.95 205.95
## + address.R          1   186.00 206.00
## - famsup.yes         1   190.02 206.02
## + Fjob.teacher       1   186.10 206.10
## + guardian.father    1   186.16 206.16
## + guardian.mother    1   186.17 206.17
## + activities.yes     1   186.20 206.20
## + reason.home        1   186.20 206.20
## + reason.reputation  1   186.21 206.21
## + internet.yes       1   186.22 206.22
## + reason.course      1   186.22 206.22
## - Mjob.health        1   190.29 206.29
## - G1                 1   191.67 207.67
## - school.GP          1   192.03 208.03
## - studytime          1   195.27 211.27
## - G3                 1   195.30 211.30
## - age                1   205.42 221.42
##
## Step:  AIC=203.24
## factor(higher) ~ G1 + age + studytime + G3 + school.GP + famsup.yes +
##     Mjob.health + schoolsup.yes + Walc
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
##                      Df Deviance    AIC
## + famrel              1   180.50 202.50
## + Fedu                1   180.69 202.69
## + Medu                1   180.74 202.74
## <none>                    183.24 203.24
## + Mjob.teacher        1   181.47 203.47
## + nursery.yes         1   181.66 203.66
## + absences            1   181.72 203.72
## + health              1   181.87 203.87
## + G2                  1   181.93 203.93
## + Pstatus.A           1   182.12 204.12
## - Walc                1   186.22 204.22
## + Fjob.health         1   182.37 204.37
## + Fjob.other          1   182.42 204.42
## + Fjob.services       1   182.43 204.43
## + failures            1   182.44 204.44
## + paid.yes            1   182.55 204.55
## + Mjob.services       1   182.57 204.57
## + Mjob.other          1   182.58 204.58
## + traveltime          1   182.62 204.62
## + freetime            1   182.67 204.67
## + famsize.GT3         1   182.89 204.89
## + sex.M               1   182.90 204.90
## + romantic.yes        1   182.96 204.96
## + goout               1   183.00 205.00
## + Fjob.teacher        1   183.00 205.00
## + guardian.mother     1   183.10 205.10
## + Dalc                1   183.12 205.12
## + address.R           1   183.12 205.12
## + reason.course       1   183.19 205.19
## + reason.home         1   183.22 205.22
## + reason.reputation   1   183.23 205.23
## + internet.yes        1   183.24 205.24
## + activities.yes      1   183.24 205.24
## + guardian.father     1   183.24 205.24
## - schoolsup.yes       1   187.25 205.25
## - Mjob.health         1   187.49 205.49
## - famsup.yes          1   187.88 205.88
## - G1                  1   188.04 206.04
## - school.GP           1   188.88 206.88
## - studytime           1   193.68 211.68
## - G3                  1   194.37 212.37
## - age                 1   202.18 220.18
##
## Step:  AIC=202.5
## factor(higher) ~ G1 + age + studytime + G3 + school.GP + famsup.yes +
##     Mjob.health + schoolsup.yes + Walc + famrel
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
##                      Df Deviance    AIC
## + Fedu                1   177.92 201.92
## + Medu                1   178.22 202.22
```

```
## + Mjob.teacher       1   178.31 202.31
## <none>                   180.50 202.50
## + freetime           1   179.06 203.06
## + nursery.yes        1   179.09 203.09
## - famrel             1   183.24 203.24
## + health             1   179.46 203.46
## + absences           1   179.48 203.48
## + G2                 1   179.49 203.49
## + Fjob.health        1   179.49 203.49
## + paid.yes           1   179.51 203.51
## + Pstatus.A          1   179.56 203.56
## + Fjob.other         1   179.62 203.62
## + Mjob.services      1   179.75 203.75
## + traveltime         1   179.88 203.88
## + Mjob.other         1   179.88 203.88
## + Fjob.services      1   179.88 203.88
## + failures           1   179.92 203.92
## - Walc               1   184.12 204.12
## + romantic.yes       1   180.13 204.13
## + address.R          1   180.15 204.15
## + Fjob.teacher       1   180.17 204.17
## + Dalc               1   180.20 204.20
## + famsize.GT3        1   180.25 204.25
## + sex.M              1   180.37 204.37
## + reason.reputation  1   180.40 204.40
## + reason.course      1   180.41 204.41
## + reason.home        1   180.42 204.42
## + internet.yes       1   180.44 204.44
## + activities.yes     1   180.45 204.45
## + guardian.mother    1   180.46 204.46
## + goout              1   180.46 204.46
## + guardian.father    1   180.49 204.49
## - schoolsup.yes      1   184.50 204.50
## - Mjob.health        1   184.66 204.66
## - famsup.yes         1   184.92 204.92
## - G1                 1   184.93 204.93
## - school.GP          1   185.44 205.44
## - G3                 1   192.09 212.09
## - studytime          1   192.51 212.51
## - age                1   199.59 219.59
##
## Step:  AIC=201.92
## factor(higher) ~ G1 + age + studytime + G3 + school.GP + famsup.yes +
##     Mjob.health + schoolsup.yes + Walc + famrel + Fedu

## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred

##                     Df Deviance    AIC
## <none>                   177.92 201.92
## - Fedu               1   180.50 202.50
## + Pstatus.A          1   176.51 202.51
## + nursery.yes        1   176.65 202.65
## + freetime           1   176.65 202.65
## - famrel             1   180.69 202.69
## + absences           1   176.84 202.84
```

```
## + paid.yes          1   176.89 202.89
## + health            1   176.97 202.97
## + Mjob.teacher      1   177.01 203.01
## + Mjob.other        1   177.06 203.06
## + Mjob.services     1   177.14 203.14
## - school.GP         1   181.15 203.15
## - Walc              1   181.22 203.22
## + G2                1   177.25 203.25
## + Fjob.health       1   177.31 203.31
## + Fjob.services     1   177.43 203.43
## + Medu              1   177.43 203.43
## + Fjob.other        1   177.49 203.49
## - famsup.yes        1   181.49 203.49
## + failures          1   177.55 203.55
## + Dalc              1   177.60 203.60
## + traveltime        1   177.60 203.60
## + guardian.mother   1   177.66 203.66
## + address.R         1   177.73 203.73
## + famsize.GT3       1   177.73 203.73
## + guardian.father   1   177.77 203.77
## + reason.reputation 1   177.78 203.78
## + internet.yes      1   177.78 203.78
## + reason.course     1   177.81 203.81
## + reason.home       1   177.83 203.83
## + sex.M             1   177.84 203.84
## + romantic.yes      1   177.87 203.87
## + activities.yes    1   177.91 203.91
## + goout             1   177.92 203.92
## + Fjob.teacher      1   177.92 203.92
## - schoolsup.yes     1   181.95 203.95
## - Mjob.health       1   182.15 204.15
## - G1                1   182.43 204.43
## - G3                1   187.34 209.34
## - studytime         1   189.00 211.00
## - age               1   195.34 217.34
```

```r
variables <- names(seleccion$coefficients)[-1]
cat("\n\nLa mejor selección de variables viene dada por: ", variables)
```

```
##
##
## La mejor selección de variables viene dada por:  G1 age studytime G3 school.GP famsup.yes Mjob.health
```

GENERACIÓN DE LOS SETS DE DATOS (train, test / Validación cruzada)

En el anterior apartado hemos obtenido las mejores variables para poder generar nuestros modelos. En este apartado lo que vamos a realizar es una división de los datos en dos sets, uno para la parte de test y otro para la parte de entrenamiento del modelo. El objetivo es utilizar el set de entrenamiento para entrenar nuestro modelo y prepararlo para la predicción y realizar pruebas para comprobar la eficacia con la que es capaz de predecir sobre nuestro set de test.

La validación de los datos la realizaremos mediante validación cruzada que lo que realiza es la selección del mejor conjunto de datos que formarán parte de cada set mediante la comprobación redundante de diferentes escenarios de manera que los datos que queden en un set y otro estén lo más balanceados posible.

Utilizaremos validación cruzada repetida dado que únicamente tenemos un set de 500 filas de datos. La generación de los sets de train y test se realiza 4 veces

```
set.seed(1234)
control<-trainControl(method = "repeatedcv",number=4,savePredictions = "all")
```

COMPARACIÓN DE MODELOS

MODELO CON REGRESIÓN LINEAL

Modelo con regresión lineal, este no tendrá rejilla porque no tiene hiperparámetros.

```
reg<- train(factor(higher)~G1+age+studytime+G3+school.GP+famsup.yes+Mjob.health+schoolsup.yes+Walc+famr
                data=students.df.s,
                method="glm",
                trControl=control,
                trace=FALSE)
reg
```

```
## Generalized Linear Model
##
## 499 samples
##  11 predictor
##   2 classes: 'No', 'Yes'
##
## No pre-processing
## Resampling: Cross-Validated (4 fold, repeated 1 times)
## Summary of sample sizes: 375, 375, 373, 374
## Resampling results:
##
##   Accuracy   Kappa
##   0.9097716  0.3866103
```

MODELO CON RED NEURONAL

Ahora vamos a generar un modelo con redes neuronales. Para comprobar su eficacia realizaremos diferentes tuneos hasta obtener el mejor resultado. La forma que tenemos de realizar el tuneado mediante el uso de una rejilla.

```
nnetgrid <-  expand.grid(size=c(1,2,3,5,10),
                         decay=c(0.01,0.1,0.001),
                         bag=FALSE)

rednnet<- train(factor(higher)~G1+age+studytime+G3+school.GP+famsup.yes+Mjob.health+schoolsup.yes+Walc+
                data=students.df.s,
                method="avNNet",linout = FALSE,
                maxit=100,
                trControl=control,
                tuneGrid=nnetgrid,
                repeats=5,
                verbose=FALSE,
                trace=FALSE)
```

```
## Warning: executing %dopar% sequentially: no parallel backend registered
```

```
rednnet
```

```
## Model Averaged Neural Network
##
```

```
## 499 samples
##  11 predictor
##   2 classes: 'No', 'Yes'
##
## No pre-processing
## Resampling: Cross-Validated (4 fold, repeated 1 times)
## Summary of sample sizes: 374, 374, 374, 375
## Resampling results across tuning parameters:
##
##   size  decay  Accuracy   Kappa
##    1    0.001  0.8957581  0.3806485
##    1    0.010  0.9017419  0.3902573
##    1    0.100  0.9017742  0.3336351
##    2    0.001  0.9097903  0.4177093
##    2    0.010  0.8977419  0.3612457
##    2    0.100  0.9138065  0.4318188
##    3    0.001  0.9117903  0.4324913
##    3    0.010  0.9138065  0.4289713
##    3    0.100  0.9138226  0.4295853
##    5    0.001  0.9057903  0.4097755
##    5    0.010  0.9017903  0.3905407
##    5    0.100  0.9058065  0.3998800
##   10    0.001  0.9037903  0.4311235
##   10    0.010  0.9017903  0.3923020
##   10    0.100  0.9037742  0.3743618
##
## Tuning parameter 'bag' was held constant at a value of FALSE
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were size = 3, decay = 0.1 and bag
##  = FALSE.
```

```
bestTuneNnet <- function(nnetmodel, size=FALSE, decay=FALSE){
  # Función que ayuda a obtener el mejor resultado obtenido en un modelo NEURAL NET
  bestSize <- rednnet$bestTune$size
  bestDecay <- rednnet$bestTune$decay
  # Cojo los parámetros de la función si están establecidos
  if (size != FALSE) {bestSize <- size}
  if (decay != FALSE) {bestDecay <- decay}
  nnetmodel$results[nnetmodel$results$size == bestSize &
                    nnetmodel$results$decay == bestDecay,]
}
```

RANDOM FOREST

```
set.seed(1234)
rfgrid<-expand.grid(mtry=c(2,3,4,5,6))

rf<- train(factor(higher)~G1+age+studytime+G3+school.GP+famsup.yes+Mjob.health+schoolsup.yes+Walc+famrel
           data=students.df.s,
           method="rf",
           trControl=control,
           tuneGrid=rfgrid,
           linout = FALSE,ntree=300,nodesize=10,
           replace=TRUE,
           importance=TRUE,
```

```r
            trace=FALSE)

rf
```

```
## Random Forest
##
## 499 samples
##  11 predictor
##   2 classes: 'No', 'Yes'
##
## No pre-processing
## Resampling: Cross-Validated (4 fold, repeated 1 times)
## Summary of sample sizes: 375, 375, 373, 374
## Resampling results across tuning parameters:
##
##   mtry  Accuracy   Kappa
##   2     0.9077394  0.2616311
##   3     0.9117394  0.3259238
##   4     0.9077711  0.3115811
##   5     0.9077550  0.3066177
##   6     0.9097552  0.3184320
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was mtry = 3.
```

```r
bestTuneRf <-  function(rfmodel, mtry=FALSE){
  # Función que ayuda a obtener el mejor resultado obtenido en un modelo RANDOM FOREST
  bMtry <- rfmodel$bestTune$mtry
  # Cojo los parámetros de la función si están establecidos
  if (mtry != FALSE) {bMtry <- mtry}
  rfmodel$results[rfmodel$results$mtry == bMtry,]
}
```

GRADIENT BOOSTING

```r
set.seed(1234)
gbmgrid<-expand.grid(shrinkage=c(0.1,0.05,0.01),
                     n.minobsinnode=c(10,20),
                     n.trees=c(100,500,1000),
                     interaction.depth=c(1,2,3))

gbm<- train(factor(higher)~G1+age+studytime+G3+school.GP+famsup.yes+Mjob.health+schoolsup.yes+Walc+famr
            data=students.df.s,
            method="gbm",
            trControl=control,
            tuneGrid=gbmgrid,
            distribution="bernoulli",
            bag.fraction=1,
            verbose=FALSE)

gbm
```

```
## Stochastic Gradient Boosting
##
## 499 samples
```

```
##  11 predictor
##   2 classes: 'No', 'Yes'
##
## No pre-processing
## Resampling: Cross-Validated (4 fold, repeated 1 times)
## Summary of sample sizes: 375, 375, 373, 374
## Resampling results across tuning parameters:
##
##   shrinkage  interaction.depth  n.minobsinnode  n.trees  Accuracy
##   0.01       1                  10               100     0.9018193
##   0.01       1                  10               500     0.9117716
##   0.01       1                  10              1000     0.9057071
##   0.01       1                  20               100     0.9018193
##   0.01       1                  20               500     0.9117716
##   0.01       1                  20              1000     0.9077552
##   0.01       2                  10               100     0.9018193
##   0.01       2                  10               500     0.9117232
##   0.01       2                  10              1000     0.9157396
##   0.01       2                  20               100     0.9018193
##   0.01       2                  20               500     0.9077391
##   0.01       2                  20              1000     0.9097552
##   0.01       3                  10               100     0.8977709
##   0.01       3                  10               500     0.9117555
##   0.01       3                  10              1000     0.9077711
##   0.01       3                  20               100     0.9018193
##   0.01       3                  20               500     0.9097552
##   0.01       3                  20              1000     0.9077870
##   0.05       1                  10               100     0.9097555
##   0.05       1                  10               500     0.8977709
##   0.05       1                  10              1000     0.8937704
##   0.05       1                  20               100     0.9097555
##   0.05       1                  20               500     0.9057714
##   0.05       1                  20              1000     0.9057552
##   0.05       2                  10               100     0.9076910
##   0.05       2                  10               500     0.9057391
##   0.05       2                  10              1000     0.9037870
##   0.05       2                  20               100     0.9097232
##   0.05       2                  20               500     0.9138193
##   0.05       2                  20              1000     0.9178036
##   0.05       3                  10               100     0.9117555
##   0.05       3                  10               500     0.8978346
##   0.05       3                  10              1000     0.8918661
##   0.05       3                  20               100     0.9117714
##   0.05       3                  20               500     0.9057867
##   0.05       3                  20              1000     0.8997545
##   0.10       1                  10               100     0.9037071
##   0.10       1                  10               500     0.8937704
##   0.10       1                  10              1000     0.8937704
##   0.10       1                  20               100     0.9057552
##   0.10       1                  20               500     0.9057552
##   0.10       1                  20              1000     0.9037870
##   0.10       2                  10               100     0.9137555
##   0.10       2                  10               500     0.9057711
##   0.10       2                  10              1000     0.8997709
```

```
##    0.10       2                     20              100     0.9077232
##    0.10       2                     20              500     0.9178356
##    0.10       2                     20             1000     0.9137875
##    0.10       3                     10              100     0.9077711
##    0.10       3                     10              500     0.8938182
##    0.10       3                     10             1000     0.8958502
##    0.10       3                     20              100     0.9077550
##    0.10       3                     20              500     0.8957384
##    0.10       3                     20             1000     0.8977386
##    Kappa
##    0.00000000
##    0.24777960
##    0.26548485
##    0.00000000
##    0.24777960
##    0.28963103
##    0.00000000
##    0.36150872
##    0.41823162
##    0.00000000
##    0.32628467
##    0.38118347
##    0.05484418
##    0.39106014
##    0.37230312
##    0.00000000
##    0.37137094
##    0.39314237
##    0.24276725
##    0.28052505
##    0.26237952
##    0.24276725
##    0.34534355
##    0.34735799
##    0.31179177
##    0.35455279
##    0.36301204
##    0.34637987
##    0.45796247
##    0.47371145
##    0.39106014
##    0.34690162
##    0.35915250
##    0.39592632
##    0.43485869
##    0.42520093
##    0.25752167
##    0.26237952
##    0.26237952
##    0.28166785
##    0.34735799
##    0.34691182
##    0.39757327
##    0.36930094
```

```
##   0.35123182
##   0.35647889
##   0.47307303
##   0.47079303
##   0.35956264
##   0.37985621
##   0.39969893
##   0.37524279
##   0.38969801
##   0.41997059
##
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were n.trees = 500,
##  interaction.depth = 2, shrinkage = 0.1 and n.minobsinnode = 20.
```

```
bestTuneGbm <-  function(gbmModel, n.trees=FALSE, shrinkage=FALSE, n.minobsinnode=FALSE, interaction.dep
  # Función que ayuda a obtener el mejor resultado obtenido en un modelo GRADIENT BOOSTING MACHINE
  bTrees <- gbmModel$bestTune$n.trees
  bShrink <- gbmModel$bestTune$shrinkage
  bMin <- gbmModel$bestTune$n.minobsinnode
  bInt <- gbmModel$bestTune$interaction.depth
  # Cojo los parámetros de la función si están establecidos
  if (n.trees != FALSE) {bTrees <- n.trees}
  if (shrinkage != FALSE) {bShrink <- shrinkage}
  if (n.minobsinnode != FALSE) {bMin <- n.minobsinnode}
  if (interaction.depth != FALSE) {bInt <- interaction.depth}
  #Devuelve el mejor resultado para los parámetros introducidos
  gbmModel$results[gbmModel$results$n.trees == bTrees &
                   gbmModel$results$shrinkage == bShrink &
                   gbmModel$results$n.minobsinnode == bMin &
                   gbmModel$results$interaction.depth == bInt,]
}
```

XGBOOST

```
set.seed(1234)
xgbmgrid<-expand.grid(
  min_child_weight=c(10),
  eta=c(0.1,0.05,0.03,0.01),
  nrounds=c(100,500,1000),
  max_depth=6,gamma=0,colsample_bytree=1,subsample=1)

xgbm<- train(factor(higher)~G1+age+studytime+G3+school.GP+famsup.yes+Mjob.health+schoolsup.yes+Walc+fam
             data=students.df.s,
             method="xgbTree",
             trControl=control,
             tuneGrid=xgbmgrid,
             verbose=FALSE)

xgbm
```

```
## eXtreme Gradient Boosting
##
## 499 samples
##  11 predictor
```

```
##   2 classes: 'No', 'Yes'
##
## No pre-processing
## Resampling: Cross-Validated (4 fold, repeated 1 times)
## Summary of sample sizes: 375, 375, 373, 374
## Resampling results across tuning parameters:
##
##   eta   nrounds  Accuracy   Kappa
##   0.01   100     0.9018193  0.00000000
##   0.01   500     0.9117878  0.22689691
##   0.01  1000     0.9177878  0.34620781
##   0.03   100     0.9018193  0.03148615
##   0.03   500     0.9137716  0.33179843
##   0.03  1000     0.9157878  0.35635381
##   0.05   100     0.9117878  0.22689691
##   0.05   500     0.9157878  0.35635381
##   0.05  1000     0.9157878  0.35635381
##   0.10   100     0.9177878  0.34620781
##   0.10   500     0.9157878  0.35635381
##   0.10  1000     0.9157878  0.35635381
##
## Tuning parameter 'max_depth' was held constant at a value of 6
##  1
## Tuning parameter 'min_child_weight' was held constant at a value of
##  10
## Tuning parameter 'subsample' was held constant at a value of 1
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were nrounds = 100, max_depth = 6,
##  eta = 0.1, gamma = 0, colsample_bytree = 1, min_child_weight = 10
##  and subsample = 1.
```

```
bestTuneXgbm <-  function(XgbmModel,
                          nrounds = FALSE,
                          max_depth = FALSE,
                          eta = FALSE,
                          gamma = FALSE,
                          colsample_bytree = FALSE,
                          min_child_weight = FALSE,
                          subsample = FALSE){

  # Función que ayuda a obtener el mejor resultado obtenido en un modelo XGBOOST

  bnrounds <- XgbmModel$bestTune$nrounds
  bmax_depth <- XgbmModel$bestTune$max_depth
  beta <- XgbmModel$bestTune$eta
  bgamma <- XgbmModel$bestTune$gamma
  bcolsample_bytree <- XgbmModel$bestTune$colsample_bytree
  bmin_child_weight <- XgbmModel$bestTune$min_child_weight
  bsubsample <- XgbmModel$bestTune$subsample

  # Cojo los parámetros de la función si están establecidos
  if (nrounds != FALSE) { bnrounds <- nrounds }
  if (max_depth != FALSE) { bmax_depth <- max_depth }
  if (eta != FALSE) { beta <- eta }
```

```r
  if (gamma != FALSE) { bgamma <- gamma }
  if (colsample_bytree != FALSE) { bcolsample_bytree <- colsample_bytree }
  if (min_child_weight != FALSE) { bmin_child_weight <- min_child_weight }
  if (subsample != FALSE) { bsubsample <- subsample }

  #Devuelve el mejor resultado para los parámetros introducidos
  XgbmModel$results[XgbmModel$results$nrounds == bnrounds &
                    XgbmModel$results$max_depth == bmax_depth &
                    XgbmModel$results$eta == beta &
                    XgbmModel$results$gamma == bgamma &
                    XgbmModel$results$colsample_bytree == bcolsample_bytree &
                    XgbmModel$results$min_child_weight == bmin_child_weight &
                    XgbmModel$results$subsample == bsubsample,]
}
```

Realizamos una comparativa de la precisión todos los modelos anteriores

```r
nnettune <- bestTuneNnet(rednnet)
rftune <- bestTuneRf(rf)
gbmtune <- bestTuneGbm(gbm)
xgbmtune <- bestTuneXgbm(xgbm)

models = c(reg$method, rednnet$method, rf$method, gbm$method, xgbm$method)
accuracies = c(reg$results$Accuracy, nnettune$Accuracy, rftune$Accuracy, gbmtune$Accuracy, xgbmtune$Accu

comparation <- data.frame("Model" = models, "Accuracy" = accuracies)
comparation[order(comparation$Accuracy, decreasing = TRUE),]
```

```
##     Model  Accuracy
## 4     gbm 0.9178356
## 5 xgbTree 0.9177878
## 2  avNNet 0.9138226
## 3      rf 0.9117394
## 1     glm 0.9097716
```

VOY POR AQUÍ, FALTA SEGUIR AJUSTANDO LOS MODELOS PARA METER LOS TUNEOS OBTENIDOS EN EL SIGUIENTE APARTADO

PREPARACIÓN DE MODELOS PARA ENSAMBLADO

```r
source ("library/cruzadas avnnet y log binaria.R")
```

```
## ------------------------------------------------------------------------

## You have loaded plyr after dplyr - this is likely to cause problems.
## If you need functions from both plyr and dplyr, please load plyr first, then dplyr:
## library(plyr); library(dplyr)

## ------------------------------------------------------------------------

##
## Attaching package: 'plyr'

## The following objects are masked from 'package:dplyr':
```

```
##
##     arrange, count, desc, failwith, id, mutate, rename, summarise,
##     summarize

##
## Attaching package: 'reshape'

## The following object is masked from 'package:dplyr':
##
##     rename

## Type 'citation("pROC")' for a citation.

##
## Attaching package: 'pROC'

## The following objects are masked from 'package:stats':
##
##     cov, smooth, var
```

```
source ("library/cruzada arbolbin.R")
```

```
## ------------------------------------------------------------------------

## You have loaded plyr after dplyr - this is likely to cause problems.
## If you need functions from both plyr and dplyr, please load plyr first, then dplyr:
## library(plyr); library(dplyr)

## ------------------------------------------------------------------------

##
## Attaching package: 'plyr'

## The following objects are masked from 'package:reshape':
##
##     rename, round_any

## The following objects are masked from 'package:dplyr':
##
##     arrange, count, desc, failwith, id, mutate, rename, summarise,
##     summarize
```

```
source ("library/cruzada rf binaria.R")
```

```
## ------------------------------------------------------------------------

## You have loaded plyr after dplyr - this is likely to cause problems.
## If you need functions from both plyr and dplyr, please load plyr first, then dplyr:
## library(plyr); library(dplyr)

## ------------------------------------------------------------------------

##
## Attaching package: 'plyr'

## The following objects are masked from 'package:reshape':
##
##     rename, round_any

## The following objects are masked from 'package:dplyr':
##
##     arrange, count, desc, failwith, id, mutate, rename, summarise,
##     summarize
```

```r
source ("library/cruzada gbm binaria.R")
```

```
## ---------------------------------------------------------------------------

## You have loaded plyr after dplyr - this is likely to cause problems.
## If you need functions from both plyr and dplyr, please load plyr first, then dplyr:
## library(plyr); library(dplyr)

## ---------------------------------------------------------------------------

##
## Attaching package: 'plyr'

## The following objects are masked from 'package:reshape':
##
##     rename, round_any

## The following objects are masked from 'package:dplyr':
##
##     arrange, count, desc, failwith, id, mutate, rename, summarise,
##     summarize
```

```r
source ("library/cruzada xgboost binaria.R")
```

```
## ---------------------------------------------------------------------------

## You have loaded plyr after dplyr - this is likely to cause problems.
## If you need functions from both plyr and dplyr, please load plyr first, then dplyr:
## library(plyr); library(dplyr)

## ---------------------------------------------------------------------------

##
## Attaching package: 'plyr'

## The following objects are masked from 'package:reshape':
##
##     rename, round_any

## The following objects are masked from 'package:dplyr':
##
##     arrange, count, desc, failwith, id, mutate, rename, summarise,
##     summarize
```

```r
source ("library/cruzada SVM binaria lineal.R")
```

```
## ---------------------------------------------------------------------------

## You have loaded plyr after dplyr - this is likely to cause problems.
## If you need functions from both plyr and dplyr, please load plyr first, then dplyr:
## library(plyr); library(dplyr)

## ---------------------------------------------------------------------------

##
## Attaching package: 'plyr'

## The following objects are masked from 'package:reshape':
##
##     rename, round_any

## The following objects are masked from 'package:dplyr':
##
```

```
##     arrange, count, desc, failwith, id, mutate, rename, summarise,
##     summarize
```

```r
source ("library/cruzada SVM binaria polinomial.R")
```

```
## ------------------------------------------------------------------------

## You have loaded plyr after dplyr - this is likely to cause problems.
## If you need functions from both plyr and dplyr, please load plyr first, then dplyr:
## library(plyr); library(dplyr)

## ------------------------------------------------------------------------

##
## Attaching package: 'plyr'

## The following objects are masked from 'package:reshape':
##
##     rename, round_any

## The following objects are masked from 'package:dplyr':
##
##     arrange, count, desc, failwith, id, mutate, rename, summarise,
##     summarize
```

```r
source ("library/cruzada SVM binaria RBF.R")
```

```
## ------------------------------------------------------------------------

## You have loaded plyr after dplyr - this is likely to cause problems.
## If you need functions from both plyr and dplyr, please load plyr first, then dplyr:
## library(plyr); library(dplyr)

## ------------------------------------------------------------------------

##
## Attaching package: 'plyr'

## The following objects are masked from 'package:reshape':
##
##     rename, round_any

## The following objects are masked from 'package:dplyr':
##
##     arrange, count, desc, failwith, id, mutate, rename, summarise,
##     summarize
```

```r
logi<-cruzadalogistica(data=students.df.s,
 vardep=vardep,listconti=variables,
 listclass=c(""), grupos=4,sinicio=1234,repe=5)
```

```
## Setting levels: control = No, case = Yes

## Setting direction: controls < cases

## Setting levels: control = No, case = Yes

## Setting direction: controls < cases

## Setting levels: control = No, case = Yes

## Setting direction: controls < cases

## Setting levels: control = No, case = Yes
```

```
## Setting direction: controls < cases
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
```

```
logi$modelo="Logística"


# Tuneamos con los datos obtenidos en el ajuste anterior
avnet<-cruzadaavnnetbin(data=students.df.s,
 vardep=vardep,listconti=variables,
 listclass=c(""), grupos=4,sinicio=1234,repe=5,
 size=c(nnettune$size),decay=c(nnettune$decay))
```

```
##
## Fitting Repeat 1
##
## # weights:  44
## initial  value 368.519001
## iter  10 value 48.275743
## iter  20 value 42.026844
## iter  30 value 40.314565
## iter  40 value 39.741220
## iter  50 value 38.245263
## iter  60 value 37.951367
## iter  70 value 37.950235
## final  value 37.949996
## converged
##
## Fitting Repeat 2
##
## # weights:  44
## initial  value 202.396507
## iter  10 value 68.101089
## iter  20 value 42.273178
## iter  30 value 39.756867
## iter  40 value 38.525904
## iter  50 value 38.468148
## final  value 38.467955
## converged
##
## Fitting Repeat 3
##
## # weights:  44
## initial  value 217.990017
## iter  10 value 72.704793
## iter  20 value 58.117095
## iter  30 value 42.373284
## iter  40 value 40.003631
## iter  50 value 39.561184
## iter  60 value 38.763794
## iter  70 value 38.591458
## iter  80 value 38.588217
## final  value 38.588182
## converged
```

```
##
## Fitting Repeat 4
##
## # weights:  44
## initial  value 161.044969
## iter  10 value 55.190403
## iter  20 value 44.628570
## iter  30 value 43.790751
## iter  40 value 43.072880
## iter  50 value 43.055732
## final  value 43.055694
## converged
##
## Fitting Repeat 5
##
## # weights:  44
## initial  value 125.054152
## iter  10 value 59.692586
## iter  20 value 39.860778
## iter  30 value 38.778177
## iter  40 value 38.651633
## iter  50 value 38.445105
## iter  60 value 38.441417
## iter  70 value 38.438713
## final  value 38.438712
## converged
##
## Fitting Repeat 1
##
## # weights:  44
## initial  value 133.314501
## iter  10 value 73.097599
## iter  20 value 43.704718
## iter  30 value 35.651606
## iter  40 value 35.133932
## iter  50 value 35.108062
## final  value 35.108050
## converged
##
## Fitting Repeat 2
##
## # weights:  44
## initial  value 108.358616
## iter  10 value 47.610433
## iter  20 value 35.621885
## iter  30 value 34.603311
## iter  40 value 34.507487
## final  value 34.507135
## converged
##
## Fitting Repeat 3
##
## # weights:  44
## initial  value 170.987871
```

```
## iter  10 value 64.913467
## iter  20 value 38.006503
## iter  30 value 34.905413
## iter  40 value 34.527510
## iter  50 value 34.507172
## final  value 34.507135
## converged
##
## Fitting Repeat 4
##
## # weights:  44
## initial  value 220.379344
## iter  10 value 63.901486
## iter  20 value 38.403029
## iter  30 value 36.613940
## iter  40 value 35.133433
## iter  50 value 34.814185
## iter  60 value 34.808009
## final  value 34.807085
## converged
##
## Fitting Repeat 5
##
## # weights:  44
## initial  value 193.739267
## iter  10 value 73.773703
## iter  20 value 55.462912
## iter  30 value 41.353741
## iter  40 value 36.272809
## iter  50 value 35.583617
## iter  60 value 35.364089
## iter  70 value 34.631001
## iter  80 value 34.471974
## final  value 34.471654
## converged
##
## Fitting Repeat 1
##
## # weights:  44
## initial  value 292.284920
## iter  10 value 76.770934
## iter  20 value 44.540103
## iter  30 value 35.575457
## iter  40 value 34.282461
## iter  50 value 33.925710
## iter  60 value 33.908519
## final  value 33.908510
## converged
##
## Fitting Repeat 2
##
## # weights:  44
## initial  value 130.044664
## iter  10 value 66.900692
```

```
## iter  20 value 36.357880
## iter  30 value 34.022521
## iter  40 value 33.922237
## iter  50 value 33.918965
## final  value 33.918964
## converged
##
## Fitting Repeat 3
##
## # weights:  44
## initial  value 167.044258
## iter  10 value 55.984662
## iter  20 value 37.123074
## iter  30 value 34.339731
## iter  40 value 33.944075
## iter  50 value 33.835812
## iter  60 value 33.829106
## final  value 33.829102
## converged
##
## Fitting Repeat 4
##
## # weights:  44
## initial  value 142.979664
## iter  10 value 45.559199
## iter  20 value 33.784041
## iter  30 value 33.379465
## iter  40 value 33.278257
## final  value 33.277945
## converged
##
## Fitting Repeat 5
##
## # weights:  44
## initial  value 174.847841
## iter  10 value 52.808989
## iter  20 value 38.961498
## iter  30 value 34.470393
## iter  40 value 33.907608
## iter  50 value 33.833501
## iter  60 value 33.828495
## final  value 33.828444
## converged
##
## Fitting Repeat 1
##
## # weights:  44
## initial  value 208.245686
## iter  10 value 54.421285
## iter  20 value 44.841333
## iter  30 value 42.005638
## iter  40 value 40.883715
## iter  50 value 40.816598
## iter  60 value 40.815895
```

```
## iter  60 value 40.815895
## iter  60 value 40.815895
## final  value 40.815895
## converged
##
## Fitting Repeat 2
##
## # weights:  44
## initial  value 287.922475
## iter  10 value 53.094174
## iter  20 value 42.448478
## iter  30 value 40.701596
## iter  40 value 40.551657
## iter  50 value 40.550178
## iter  50 value 40.550177
## iter  50 value 40.550177
## final  value 40.550177
## converged
##
## Fitting Repeat 3
##
## # weights:  44
## initial  value 307.277926
## iter  10 value 57.334636
## iter  20 value 45.456046
## iter  30 value 41.871945
## iter  40 value 41.111021
## iter  50 value 40.354103
## iter  60 value 40.326485
## final  value 40.326338
## converged
##
## Fitting Repeat 4
##
## # weights:  44
## initial  value 193.209892
## iter  10 value 76.880351
## iter  20 value 46.427051
## iter  30 value 42.245951
## iter  40 value 41.228388
## iter  50 value 40.898395
## iter  60 value 40.850872
## iter  70 value 40.835068
## final  value 40.835066
## converged
##
## Fitting Repeat 5
##
## # weights:  44
## initial  value 167.839877
## iter  10 value 58.674069
## iter  20 value 41.694662
## iter  30 value 40.855548
## iter  40 value 40.835194
```

```
## final  value 40.835066
## converged
##
## Fitting Repeat 1
##
## # weights:  44
## initial  value 101.268287
## iter  10 value 61.384358
## iter  20 value 43.701537
## iter  30 value 41.584426
## iter  40 value 41.430559
## iter  50 value 39.780839
## iter  60 value 39.612234
## iter  70 value 39.515215
## iter  80 value 39.504466
## final  value 39.504464
## converged
##
## Fitting Repeat 2
##
## # weights:  44
## initial  value 220.928137
## iter  10 value 55.692548
## iter  20 value 42.193870
## iter  30 value 40.724444
## iter  40 value 40.226143
## iter  50 value 40.214315
## final  value 40.214247
## converged
##
## Fitting Repeat 3
##
## # weights:  44
## initial  value 121.672405
## iter  10 value 52.998853
## iter  20 value 41.121048
## iter  30 value 39.694372
## iter  40 value 39.654604
## final  value 39.654236
## converged
##
## Fitting Repeat 4
##
## # weights:  44
## initial  value 203.480939
## iter  10 value 72.402183
## iter  20 value 47.295042
## iter  30 value 42.469585
## iter  40 value 39.823239
## iter  50 value 39.556494
## iter  60 value 39.521623
## final  value 39.521523
## converged
##
```

```
## Fitting Repeat 5
##
## # weights:  44
## initial  value 254.333903
## iter  10 value 62.614258
## iter  20 value 43.529838
## iter  30 value 39.885250
## iter  40 value 39.533268
## iter  50 value 39.504524
## final  value 39.504463
## converged
##
## Fitting Repeat 1
##
## # weights:  44
## initial  value 204.282269
## iter  10 value 58.778121
## iter  20 value 38.542330
## iter  30 value 36.297642
## iter  40 value 35.762580
## iter  50 value 35.752083
## final  value 35.752059
## converged
##
## Fitting Repeat 2
##
## # weights:  44
## initial  value 327.331106
## iter  10 value 55.059176
## iter  20 value 37.361441
## iter  30 value 35.973586
## iter  40 value 35.696776
## iter  50 value 35.667940
## iter  60 value 35.643556
## iter  70 value 35.643286
## final  value 35.643285
## converged
##
## Fitting Repeat 3
##
## # weights:  44
## initial  value 125.757081
## iter  10 value 54.019101
## iter  20 value 38.541837
## iter  30 value 36.099965
## iter  40 value 35.758668
## iter  50 value 35.752128
## final  value 35.752059
## converged
##
## Fitting Repeat 4
##
## # weights:  44
## initial  value 177.569527
```

```
## iter  10 value 61.799071
## iter  20 value 42.879850
## iter  30 value 38.126899
## iter  40 value 36.986866
## iter  50 value 36.168846
## iter  60 value 35.766351
## iter  70 value 35.755273
## iter  80 value 35.752084
## final  value 35.752059
## converged
##
## Fitting Repeat 5
##
## # weights:  44
## initial  value 280.868688
## iter  10 value 56.327625
## iter  20 value 38.974785
## iter  30 value 36.409428
## iter  40 value 35.841756
## iter  50 value 35.762884
## iter  60 value 35.756866
## iter  70 value 35.754450
## iter  80 value 35.752144
## iter  90 value 35.752059
## iter  90 value 35.752059
## iter  90 value 35.752059
## final  value 35.752059
## converged
##
## Fitting Repeat 1
##
## # weights:  44
## initial  value 231.618766
## iter  10 value 55.700972
## iter  20 value 42.141946
## iter  30 value 39.487008
## iter  40 value 38.625938
## iter  50 value 38.346974
## iter  60 value 37.687701
## iter  70 value 37.670569
## final  value 37.670509
## converged
##
## Fitting Repeat 2
##
## # weights:  44
## initial  value 257.689157
## iter  10 value 66.582709
## iter  20 value 42.903137
## iter  30 value 38.921362
## iter  40 value 38.005256
## iter  50 value 37.670955
## iter  60 value 37.635126
## iter  70 value 37.634842
```

```
## iter  70 value 37.634842
## iter  70 value 37.634842
## final  value 37.634842
## converged
##
## Fitting Repeat 3
##
## # weights:  44
## initial  value 157.306631
## iter  10 value 65.383307
## iter  20 value 41.342361
## iter  30 value 39.636467
## iter  40 value 38.840501
## iter  50 value 38.626688
## iter  60 value 38.624057
## final  value 38.623788
## converged
##
## Fitting Repeat 4
##
## # weights:  44
## initial  value 274.438968
## iter  10 value 52.073776
## iter  20 value 42.849316
## iter  30 value 39.386796
## iter  40 value 37.775710
## iter  50 value 37.670631
## final  value 37.670509
## converged
##
## Fitting Repeat 5
##
## # weights:  44
## initial  value 296.366916
## iter  10 value 59.151807
## iter  20 value 40.328991
## iter  30 value 38.616672
## iter  40 value 38.221005
## iter  50 value 37.962719
## iter  60 value 37.956217
## final  value 37.956210
## converged
##
## Fitting Repeat 1
##
## # weights:  44
## initial  value 300.413510
## iter  10 value 56.411508
## iter  20 value 42.517268
## iter  30 value 38.571796
## iter  40 value 38.390053
## iter  50 value 37.987487
## iter  60 value 37.941428
## iter  70 value 37.910976
```

```
## final  value 37.910795
## converged
##
## Fitting Repeat 2
##
## # weights:  44
## initial  value 293.605138
## iter  10 value 58.745229
## iter  20 value 42.539751
## iter  30 value 37.631381
## iter  40 value 37.056072
## iter  50 value 36.905529
## iter  60 value 36.858633
## iter  70 value 36.858433
## final  value 36.858432
## converged
##
## Fitting Repeat 3
##
## # weights:  44
## initial  value 273.250190
## iter  10 value 65.664339
## iter  20 value 47.062040
## iter  30 value 38.662624
## iter  40 value 37.071290
## iter  50 value 36.647775
## iter  60 value 36.639645
## final  value 36.639643
## converged
##
## Fitting Repeat 4
##
## # weights:  44
## initial  value 139.758951
## iter  10 value 49.980696
## iter  20 value 37.896185
## iter  30 value 37.059217
## iter  40 value 37.054587
## final  value 37.054571
## converged
##
## Fitting Repeat 5
##
## # weights:  44
## initial  value 149.592706
## iter  10 value 56.773270
## iter  20 value 38.824826
## iter  30 value 37.428304
## iter  40 value 37.208067
## iter  50 value 37.205415
## final  value 37.205408
## converged
##
## Fitting Repeat 1
```

```
##
## # weights:  44
## initial  value 202.846035
## iter  10 value 62.384368
## iter  20 value 40.879027
## iter  30 value 39.169553
## iter  40 value 39.104616
## iter  50 value 39.102544
## iter  50 value 39.102543
## iter  50 value 39.102543
## final  value 39.102543
## converged
##
## Fitting Repeat 2
##
## # weights:  44
## initial  value 178.478896
## iter  10 value 61.215340
## iter  20 value 41.451175
## iter  30 value 37.186225
## iter  40 value 36.914899
## iter  50 value 36.899821
## final  value 36.899788
## converged
##
## Fitting Repeat 3
##
## # weights:  44
## initial  value 236.702694
## iter  10 value 61.962193
## iter  20 value 41.496300
## iter  30 value 38.785384
## iter  40 value 38.126577
## iter  50 value 37.902954
## iter  60 value 37.902466
## iter  60 value 37.902465
## iter  60 value 37.902465
## final  value 37.902465
## converged
##
## Fitting Repeat 4
##
## # weights:  44
## initial  value 230.526424
## iter  10 value 73.635201
## iter  20 value 44.978416
## iter  30 value 40.506838
## iter  40 value 37.756351
## iter  50 value 37.370700
## iter  60 value 37.350367
## final  value 37.350336
## converged
##
## Fitting Repeat 5
```

```
##
## # weights:  44
## initial  value 214.918935
## iter  10 value 57.435067
## iter  20 value 41.936412
## iter  30 value 38.079142
## iter  40 value 37.322771
## iter  50 value 37.243659
## iter  60 value 37.228752
## iter  70 value 37.102827
## iter  80 value 37.091508
## final  value 37.091461
## converged
##
## Fitting Repeat 1
##
## # weights:  44
## initial  value 199.573096
## iter  10 value 48.028957
## iter  20 value 37.449940
## iter  30 value 35.720762
## iter  40 value 35.622246
## iter  50 value 35.611001
## final  value 35.610872
## converged
##
## Fitting Repeat 2
##
## # weights:  44
## initial  value 210.507583
## iter  10 value 55.436016
## iter  20 value 37.443291
## iter  30 value 36.122022
## iter  40 value 35.865610
## iter  50 value 35.635359
## iter  60 value 35.042452
## iter  70 value 35.030912
## final  value 35.030896
## converged
##
## Fitting Repeat 3
##
## # weights:  44
## initial  value 201.043940
## iter  10 value 52.743454
## iter  20 value 38.767042
## iter  30 value 36.144933
## iter  40 value 35.629930
## iter  50 value 35.611407
## final  value 35.610871
## converged
##
## Fitting Repeat 4
##
```

```
## # weights:  44
## initial  value 215.039421
## iter  10 value 58.402052
## iter  20 value 43.068259
## iter  30 value 37.292901
## iter  40 value 35.659441
## iter  50 value 35.504809
## iter  60 value 35.320648
## iter  70 value 35.253452
## final  value 35.253346
## converged
##
## Fitting Repeat 5
##
## # weights:  44
## initial  value 132.381771
## iter  10 value 56.681803
## iter  20 value 39.799473
## iter  30 value 36.396583
## iter  40 value 35.061436
## iter  50 value 34.793739
## iter  60 value 34.785098
## iter  70 value 34.784963
## final  value 34.784962
## converged
##
## Fitting Repeat 1
##
## # weights:  44
## initial  value 109.644873
## iter  10 value 65.786215
## iter  20 value 43.887415
## iter  30 value 38.864788
## iter  40 value 38.341537
## iter  50 value 38.260525
## iter  60 value 38.239096
## iter  70 value 38.210486
## final  value 38.209814
## converged
##
## Fitting Repeat 2
##
## # weights:  44
## initial  value 196.159932
## iter  10 value 55.485149
## iter  20 value 40.433104
## iter  30 value 37.904051
## iter  40 value 37.765763
## iter  50 value 37.756390
## final  value 37.756363
## converged
##
## Fitting Repeat 3
##
```

```
## # weights:  44
## initial  value 309.594745
## iter  10 value 56.249811
## iter  20 value 44.530297
## iter  30 value 39.496436
## iter  40 value 38.551614
## iter  50 value 38.196751
## iter  60 value 38.193807
## final  value 38.193799
## converged
##
## Fitting Repeat 4
##
## # weights:  44
## initial  value 167.313779
## iter  10 value 62.756787
## iter  20 value 41.261469
## iter  30 value 38.426951
## iter  40 value 38.380565
## iter  50 value 38.377322
## final  value 38.377320
## converged
##
## Fitting Repeat 5
##
## # weights:  44
## initial  value 222.469479
## iter  10 value 64.924589
## iter  20 value 46.884130
## iter  30 value 41.017191
## iter  40 value 39.474349
## iter  50 value 38.167021
## iter  60 value 37.914617
## iter  70 value 37.773388
## iter  80 value 37.759055
## iter  90 value 37.757532
## iter 100 value 37.757448
## final  value 37.757448
## stopped after 100 iterations
##
## Fitting Repeat 1
##
## # weights:  44
## initial  value 129.638510
## iter  10 value 60.585432
## iter  20 value 43.340143
## iter  30 value 38.048164
## iter  40 value 37.583923
## final  value 37.583287
## converged
##
## Fitting Repeat 2
##
## # weights:  44
```

```
## initial  value 177.563836
## iter  10 value 57.480195
## iter  20 value 40.296570
## iter  30 value 38.711150
## iter  40 value 38.033099
## iter  50 value 37.777965
## iter  60 value 37.589035
## iter  70 value 37.577727
## iter  80 value 37.563709
## iter  90 value 37.563288
## final  value 37.563287
## converged
##
## Fitting Repeat 3
##
## # weights:  44
## initial  value 234.570447
## iter  10 value 58.801040
## iter  20 value 43.461803
## iter  30 value 40.587630
## iter  40 value 40.282186
## iter  50 value 40.273623
## iter  60 value 40.243423
## iter  70 value 40.035694
## iter  80 value 39.743748
## iter  90 value 39.730503
## final  value 39.726205
## converged
##
## Fitting Repeat 4
##
## # weights:  44
## initial  value 165.262978
## iter  10 value 67.131976
## iter  20 value 42.172051
## iter  30 value 39.116466
## iter  40 value 38.376242
## iter  50 value 37.564615
## iter  60 value 37.522617
## final  value 37.522582
## converged
##
## Fitting Repeat 5
##
## # weights:  44
## initial  value 119.295008
## iter  10 value 48.964377
## iter  20 value 38.853232
## iter  30 value 38.062117
## iter  40 value 37.844171
## iter  50 value 37.587556
## iter  60 value 37.563314
## final  value 37.563287
## converged
```

```
##
## Fitting Repeat 1
##
## # weights:  44
## initial  value 178.601823
## iter  10 value 65.217890
## iter  20 value 41.479777
## iter  30 value 38.060150
## iter  40 value 37.766286
## iter  50 value 37.622193
## iter  60 value 37.431115
## final  value 37.430801
## converged
##
## Fitting Repeat 2
##
## # weights:  44
## initial  value 258.368057
## iter  10 value 62.193473
## iter  20 value 43.232761
## iter  30 value 39.479234
## iter  40 value 37.737399
## iter  50 value 37.454061
## iter  60 value 37.402743
## final  value 37.395450
## converged
##
## Fitting Repeat 3
##
## # weights:  44
## initial  value 221.450474
## iter  10 value 72.521896
## iter  20 value 41.675449
## iter  30 value 38.343195
## iter  40 value 37.653761
## iter  50 value 37.432273
## iter  60 value 37.430801
## iter  60 value 37.430800
## iter  60 value 37.430800
## final  value 37.430800
## converged
##
## Fitting Repeat 4
##
## # weights:  44
## initial  value 161.019341
## iter  10 value 49.756271
## iter  20 value 38.680331
## iter  30 value 37.672053
## iter  40 value 37.231773
## iter  50 value 37.132718
## iter  60 value 37.117161
## final  value 37.117153
## converged
```

```
##
## Fitting Repeat 5
##
## # weights:  44
## initial  value 199.917522
## iter  10 value 58.390353
## iter  20 value 42.333601
## iter  30 value 39.257534
## iter  40 value 38.479657
## iter  50 value 37.398975
## iter  60 value 37.207121
## iter  70 value 37.118321
## final  value 37.117153
## converged
##
## Fitting Repeat 1
##
## # weights:  44
## initial  value 160.855503
## iter  10 value 56.492968
## iter  20 value 42.320447
## iter  30 value 39.514363
## iter  40 value 38.523879
## iter  50 value 38.396977
## iter  60 value 38.358748
## final  value 38.358534
## converged
##
## Fitting Repeat 2
##
## # weights:  44
## initial  value 166.604782
## iter  10 value 75.410392
## iter  20 value 50.622600
## iter  30 value 45.525869
## iter  40 value 40.265607
## iter  50 value 38.437899
## iter  60 value 38.209160
## iter  70 value 38.202906
## final  value 38.202902
## converged
##
## Fitting Repeat 3
##
## # weights:  44
## initial  value 122.308423
## iter  10 value 58.013790
## iter  20 value 44.478301
## iter  30 value 39.662185
## iter  40 value 38.377253
## iter  50 value 37.759527
## iter  60 value 37.602116
## iter  70 value 37.600324
## final  value 37.600314
```

```
## converged
##
## Fitting Repeat 4
##
## # weights:  44
## initial  value 279.097880
## iter  10 value 62.037054
## iter  20 value 40.405247
## iter  30 value 38.141625
## iter  40 value 38.041989
## iter  50 value 38.033638
## final  value 38.033634
## converged
##
## Fitting Repeat 5
##
## # weights:  44
## initial  value 204.123360
## iter  10 value 58.954838
## iter  20 value 41.431020
## iter  30 value 38.967795
## iter  40 value 38.022337
## iter  50 value 37.616162
## iter  60 value 37.600317
## final  value 37.600314
## converged
##
## Fitting Repeat 1
##
## # weights:  44
## initial  value 242.133450
## iter  10 value 67.937001
## iter  20 value 44.976757
## iter  30 value 37.952719
## iter  40 value 37.671894
## iter  50 value 37.455417
## iter  60 value 37.368937
## iter  70 value 37.357129
## final  value 37.356884
## converged
##
## Fitting Repeat 2
##
## # weights:  44
## initial  value 257.005385
## iter  10 value 57.024461
## iter  20 value 38.818377
## iter  30 value 37.432221
## iter  40 value 37.175394
## iter  50 value 37.163676
## final  value 37.163667
## converged
##
## Fitting Repeat 3
```

```
##
## # weights:  44
## initial  value 248.250093
## iter  10 value 60.774450
## iter  20 value 41.310193
## iter  30 value 37.713943
## iter  40 value 37.193151
## iter  50 value 37.163914
## iter  60 value 37.163668
## final  value 37.163667
## converged
##
## Fitting Repeat 4
##
## # weights:  44
## initial  value 256.389914
## iter  10 value 51.441035
## iter  20 value 39.182927
## iter  30 value 37.080585
## iter  40 value 36.151519
## iter  50 value 36.076566
## iter  60 value 36.042203
## final  value 36.042134
## converged
##
## Fitting Repeat 5
##
## # weights:  44
## initial  value 259.853237
## iter  10 value 48.174908
## iter  20 value 40.432015
## iter  30 value 37.284567
## iter  40 value 37.008806
## iter  50 value 37.005137
## final  value 37.005131
## converged
##
## Fitting Repeat 1
##
## # weights:  44
## initial  value 204.855865
## iter  10 value 65.023167
## iter  20 value 38.102221
## iter  30 value 36.742557
## iter  40 value 36.527184
## iter  50 value 36.502870
## final  value 36.502818
## converged
##
## Fitting Repeat 2
##
## # weights:  44
## initial  value 122.551090
## iter  10 value 63.487240
```

```
## iter  20 value 39.842981
## iter  30 value 36.963402
## iter  40 value 36.081063
## iter  50 value 35.910983
## iter  60 value 35.910607
## final  value 35.910605
## converged
##
## Fitting Repeat 3
##
## # weights:  44
## initial  value 166.149555
## iter  10 value 55.333405
## iter  20 value 38.724316
## iter  30 value 37.042319
## iter  40 value 36.322964
## iter  50 value 36.261041
## iter  60 value 36.257949
## final  value 36.257935
## converged
##
## Fitting Repeat 4
##
## # weights:  44
## initial  value 191.233778
## iter  10 value 67.840501
## iter  20 value 41.827825
## iter  30 value 36.851395
## iter  40 value 36.203510
## iter  50 value 36.121689
## iter  60 value 36.097358
## final  value 36.097292
## converged
##
## Fitting Repeat 5
##
## # weights:  44
## initial  value 225.505068
## iter  10 value 60.074617
## iter  20 value 39.512483
## iter  30 value 36.681840
## iter  40 value 36.145623
## iter  50 value 36.082538
## iter  60 value 35.979750
## final  value 35.979403
## converged
##
## Fitting Repeat 1
##
## # weights:  44
## initial  value 173.952782
## iter  10 value 57.707819
## iter  20 value 42.287645
## iter  30 value 37.783996
```

```
## iter  40 value 37.251320
## iter  50 value 37.085268
## iter  60 value 37.084073
## final  value 37.084072
## converged
##
## Fitting Repeat 2
##
## # weights:  44
## initial  value 236.262185
## iter  10 value 74.865281
## iter  20 value 51.421370
## iter  30 value 38.921194
## iter  40 value 37.335279
## iter  50 value 36.854445
## iter  60 value 36.827489
## final  value 36.827317
## converged
##
## Fitting Repeat 3
##
## # weights:  44
## initial  value 189.929516
## iter  10 value 54.966627
## iter  20 value 39.095089
## iter  30 value 37.921144
## iter  40 value 37.398214
## iter  50 value 37.329172
## iter  60 value 37.327963
## final  value 37.327957
## converged
##
## Fitting Repeat 4
##
## # weights:  44
## initial  value 321.234541
## iter  10 value 52.447297
## iter  20 value 38.698155
## iter  30 value 37.495563
## iter  40 value 37.236034
## iter  50 value 37.234185
## iter  50 value 37.234185
## iter  50 value 37.234185
## final  value 37.234185
## converged
##
## Fitting Repeat 5
##
## # weights:  44
## initial  value 281.102085
## iter  10 value 54.460896
## iter  20 value 43.031712
## iter  30 value 41.792394
## iter  40 value 38.652366
```

```
## iter  50 value 37.048226
## iter  60 value 36.869436
## iter  70 value 36.866547
## final  value 36.866546
## converged
##
## Fitting Repeat 1
##
## # weights:  44
## initial  value 212.325687
## iter  10 value 50.348840
## iter  20 value 40.984246
## iter  30 value 39.476377
## iter  40 value 39.417796
## final  value 39.417539
## converged
##
## Fitting Repeat 2
##
## # weights:  44
## initial  value 219.945615
## iter  10 value 50.159213
## iter  20 value 41.372787
## iter  30 value 39.731794
## iter  40 value 39.423915
## iter  50 value 39.417541
## final  value 39.417539
## converged
##
## Fitting Repeat 3
##
## # weights:  44
## initial  value 188.646374
## iter  10 value 58.388483
## iter  20 value 42.872550
## iter  30 value 40.804127
## iter  40 value 40.637774
## iter  50 value 40.632085
## final  value 40.632054
## converged
##
## Fitting Repeat 4
##
## # weights:  44
## initial  value 265.628311
## iter  10 value 68.883317
## iter  20 value 52.547224
## iter  30 value 45.653664
## iter  40 value 41.629003
## iter  50 value 40.055046
## iter  60 value 39.611783
## iter  70 value 39.505734
## iter  80 value 39.503437
## final  value 39.503433
```

```
## converged
##
## Fitting Repeat 5
##
## # weights:  44
## initial  value 92.727474
## iter  10 value 50.796500
## iter  20 value 42.269129
## iter  30 value 40.132845
## iter  40 value 39.439794
## iter  50 value 39.367855
## iter  60 value 39.363276
## final  value 39.363274
## converged
##
## Fitting Repeat 1
##
## # weights:  44
## initial  value 227.205324
## iter  10 value 78.822460
## iter  20 value 46.970799
## iter  30 value 38.710263
## iter  40 value 37.588361
## iter  50 value 37.388525
## iter  60 value 37.372110
## final  value 37.372073
## converged
##
## Fitting Repeat 2
##
## # weights:  44
## initial  value 269.599019
## iter  10 value 60.230695
## iter  20 value 40.980739
## iter  30 value 39.177964
## iter  40 value 38.405826
## iter  50 value 37.534207
## iter  60 value 36.930214
## iter  70 value 36.927168
## final  value 36.927164
## converged
##
## Fitting Repeat 3
##
## # weights:  44
## initial  value 219.145486
## iter  10 value 59.714804
## iter  20 value 40.404807
## iter  30 value 37.793363
## iter  40 value 37.372437
## iter  50 value 37.358325
## final  value 37.358319
## converged
##
```

```
## Fitting Repeat 4
##
## # weights:  44
## initial  value 230.381953
## iter  10 value 64.150423
## iter  20 value 39.456021
## iter  30 value 38.171581
## iter  40 value 37.186040
## iter  50 value 36.950933
## iter  60 value 36.928461
## final  value 36.928440
## converged
##
## Fitting Repeat 5
##
## # weights:  44
## initial  value 206.313506
## iter  10 value 53.697232
## iter  20 value 39.732412
## iter  30 value 37.922373
## iter  40 value 37.627502
## iter  50 value 37.619879
## final  value 37.619855
## converged
##
## Fitting Repeat 1
##
## # weights:  44
## initial  value 272.715787
## iter  10 value 77.426515
## iter  20 value 41.298206
## iter  30 value 35.431990
## iter  40 value 34.945099
## iter  50 value 34.939714
## final  value 34.939697
## converged
##
## Fitting Repeat 2
##
## # weights:  44
## initial  value 263.877048
## iter  10 value 52.931004
## iter  20 value 38.391195
## iter  30 value 35.607039
## iter  40 value 34.793147
## iter  50 value 34.770632
## final  value 34.770561
## converged
##
## Fitting Repeat 3
##
## # weights:  44
## initial  value 173.232712
## iter  10 value 62.272014
```

```
## iter  20 value 39.318441
## iter  30 value 35.722354
## iter  40 value 34.977645
## iter  50 value 34.940785
## iter  60 value 34.924364
## iter  70 value 34.499806
## iter  80 value 34.451501
## final  value 34.450561
## converged
##
## Fitting Repeat 4
##
## # weights:  44
## initial  value 239.401265
## iter  10 value 47.904992
## iter  20 value 37.376139
## iter  30 value 36.664210
## iter  40 value 35.313120
## iter  50 value 35.198821
## final  value 35.198550
## converged
##
## Fitting Repeat 5
##
## # weights:  44
## initial  value 209.809157
## iter  10 value 59.166713
## iter  20 value 37.255042
## iter  30 value 36.359339
## iter  40 value 35.281771
## iter  50 value 34.799888
## iter  60 value 34.770576
## final  value 34.770561
## converged
##
## Fitting Repeat 1
##
## # weights:  44
## initial  value 506.046567
## iter  10 value 89.915458
## iter  20 value 64.632778
## iter  30 value 59.568381
## iter  40 value 57.673989
## iter  50 value 51.529777
## iter  60 value 50.240924
## iter  70 value 49.854736
## iter  80 value 49.761762
## iter  90 value 49.761125
## final  value 49.761119
## converged
##
## Fitting Repeat 2
##
## # weights:  44
```

```
## initial  value 163.665474
## iter  10 value 88.337130
## iter  20 value 52.784784
## iter  30 value 49.583276
## iter  40 value 49.459676
## iter  50 value 49.457167
## final  value 49.457150
## converged
##
## Fitting Repeat 3
##
## # weights:  44
## initial  value 246.670200
## iter  10 value 78.740318
## iter  20 value 56.057565
## iter  30 value 50.316657
## iter  40 value 49.817122
## iter  50 value 49.734862
## iter  60 value 48.951182
## iter  70 value 48.711763
## iter  80 value 48.441297
## final  value 48.440838
## converged
##
## Fitting Repeat 4
##
## # weights:  44
## initial  value 305.012654
## iter  10 value 70.087107
## iter  20 value 54.120081
## iter  30 value 51.857717
## iter  40 value 51.013582
## iter  50 value 50.643868
## iter  60 value 50.603459
## iter  70 value 50.579951
## final  value 50.579787
## converged
##
## Fitting Repeat 5
##
## # weights:  44
## initial  value 336.139689
## iter  10 value 66.752688
## iter  20 value 54.095522
## iter  30 value 50.626735
## iter  40 value 49.890195
## iter  50 value 49.816600
## iter  60 value 49.815571
## iter  60 value 49.815571
## iter  60 value 49.815571
## final  value 49.815571
## converged
##   size decay   bag  Accuracy     Kappa AccuracySD   KappaSD
## 1    3   0.1 FALSE 0.9110182 0.4071574 0.01723245 0.1705323
```

```
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
```

```
avnet$modelo="AvNet"


arbol<-cruzadaarbolbin(data=students.df.s,
 vardep=vardep,listconti=variables,
 listclass=c(""), grupos=4,sinicio=1234,repe=5)
```

```
##   cp  Accuracy     Kappa AccuracySD   KappaSD
## 1  0 0.8961793 0.2580466 0.01661613 0.1668027
```

```
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
```

```
arbol$modelo="Árbol"


bag<-cruzadarfbin(data=students.df.s,
  vardep=vardep,listconti=variables,
  listclass=c(""),
  grupos=4,sinicio=1234,repe=5,nodesize=10,
  ntree=1000,replace=TRUE,
  mtry=rftune$mtry)
```

```
##   mtry  Accuracy     Kappa AccuracySD  KappaSD
## 1    3 0.9078214 0.2803234 0.01770944 0.175194
```

```
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
## Setting levels: control = No, case = Yes
```

```
## Setting direction: controls < cases
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
```

```
bag$modelo="Bag"


rf<-cruzadarfbin(data=students.df.s, vardep=vardep,
 listconti=variables, listclass=c(""),
 grupos=4,sinicio=1234,repe=5,nodesize=10,
 mtry=6,ntree=3000,replace=TRUE,sampsize=150)
```

```
##   mtry  Accuracy    Kappa AccuracySD   KappaSD
## 1    6 0.9054183 0.294027  0.0191713 0.1786822
```

```
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
```

```
rf$modelo="RF"


gbm<-cruzadagbmbin(data=students.df.s,
  vardep=vardep,listconti=variables,
  listclass=c(""),
  grupos=4,sinicio=1234,repe=5,
  n.minobsinnode=gbmtune$n.minobsinnode,
  shrinkage=gbmtune$shrinkage,
  n.trees=gbmtune$n.trees,
  interaction.depth=gbmtune$interaction.depth)
```

```
##   n.minobsinnode shrinkage n.trees interaction.depth  Accuracy     Kappa
## 1             20       0.1     500                 2 0.9134151 0.4373928
##   AccuracySD   KappaSD
## 1 0.01580442 0.1427231
```

```
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
```

```
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
```

```r
gbm$modelo="gbm"


xgbm<-cruzadaxgbmbin(data=students.df.s,
 vardep=vardep,listconti=variables,
  listclass=c(""),
  grupos=4,sinicio=1234,repe=5,
  min_child_weight=xgbmtune$min_child_weight,
  eta=xgbmtune$eta,
  nrounds=xgbmtune$nrounds,
  max_depth=xgbmtune$max_depth,
  gamma=xgbmtune$gamma,
  colsample_bytree=xgbmtune$colsample_bytree,
  subsample=xgbmtune$subsample)
```

```
## Warning in check.booster.params(params, ...): The following parameters were provided multiple times:
##  objective
##   Only the last value for each of them will be used.

## Warning in check.booster.params(params, ...): The following parameters were provided multiple times:
##  objective
##   Only the last value for each of them will be used.

## Warning in check.booster.params(params, ...): The following parameters were provided multiple times:
##  objective
##   Only the last value for each of them will be used.

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##  objective
##   Only the last value for each of them will be used.

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##  objective
##   Only the last value for each of them will be used.

## Warning in check.booster.params(params, ...): The following parameters were provided multiple times:
##  objective
##   Only the last value for each of them will be used.
```

```
## Warning in check.booster.params(params, ...): The following parameters were provided multiple times:
##  objective
##   Only the last value for each of them will be used.

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##  objective
##   Only the last value for each of them will be used.

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##  objective
##   Only the last value for each of them will be used.

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##  objective
##   Only the last value for each of them will be used.

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##  objective
##   Only the last value for each of them will be used.

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##  objective
##   Only the last value for each of them will be used.

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##  objective
##   Only the last value for each of them will be used.

## Warning in check.booster.params(params, ...): The following parameters were provided multiple times:
##  objective
##   Only the last value for each of them will be used.

## Warning in check.booster.params(params, ...): The following parameters were provided multiple times:
##  objective
##   Only the last value for each of them will be used.

## Warning in check.booster.params(params, ...): The following parameters were provided multiple times:
##  objective
##   Only the last value for each of them will be used.

## Warning in check.booster.params(params, ...): The following parameters were provided multiple times:
##  objective
##   Only the last value for each of them will be used.

## Warning in check.booster.params(params, ...): The following parameters were provided multiple times:
##  objective
##   Only the last value for each of them will be used.

## Warning in check.booster.params(params, ...): The following parameters were provided multiple times:
##  objective
##   Only the last value for each of them will be used.

## Warning in check.booster.params(params, ...): The following parameters were provided multiple times:
```

```
##  objective
##   Only the last value for each of them will be used.
```

```
##   min_child_weight eta nrounds max_depth gamma colsample_bytree subsample
## 1                10 0.1     100         6     0                1         1
##     Accuracy     Kappa AccuracySD   KappaSD
## 1 0.9126055 0.323598 0.01693507 0.1871463
```

```
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
```

```
## Setting levels: control = No, case = Yes
```

```
## Setting direction: controls < cases
```

```
## Setting levels: control = No, case = Yes
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```
## Setting direction: controls < cases
```

```
## Setting levels: control = No, case = Yes
```

```
## Setting direction: controls < cases
```

```
## Setting levels: control = No, case = Yes
```

```
## Setting direction: controls < cases
```

```
xgbm$modelo="xgbm"

svm<-cruzadaSVMbin(data=students.df.s,
 vardep=vardep,listconti=variables,
listclass=c(""),
  grupos=4,sinicio=1234,repe=5,C=0.01)
```

```
##      C  Accuracy     Kappa AccuracySD   KappaSD
## 1 0.01 0.9037924 0.2519177 0.01482343 0.1600169
```

```
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
```

```
## Setting levels: control = No, case = Yes
```

```
## Setting direction: controls < cases
```

```
## Setting levels: control = No, case = Yes
```

```
## Setting direction: controls < cases
```

```
## Setting levels: control = No, case = Yes
```

```
## Setting direction: controls < cases
```

```
## Setting levels: control = No, case = Yes
```

```
## Setting direction: controls < cases
```

```
svm$modelo="SVM"


svmp<-cruzadaSVMbinPoly(data=students.df.s,
 vardep=vardep,listconti=variables,
listclass=c(""),
  grupos=4,sinicio=1234,repe=5,C=2,degree=3,scale=0.1)
```

```
##   C degree scale  Accuracy     Kappa  AccuracySD  KappaSD
## 1 2      3   0.1 0.9086214 0.2005234 0.009123285 0.162453
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
```

```
svmp$modelo="SVMPoly"


svmrbf<-cruzadaSVMbinRBF(data=students.df.s, vardep=vardep,
   listconti=variables,
 listclass=c(""),
  grupos=4,sinicio=1234,repe=5,
  C=1,sigma=0.1)
```

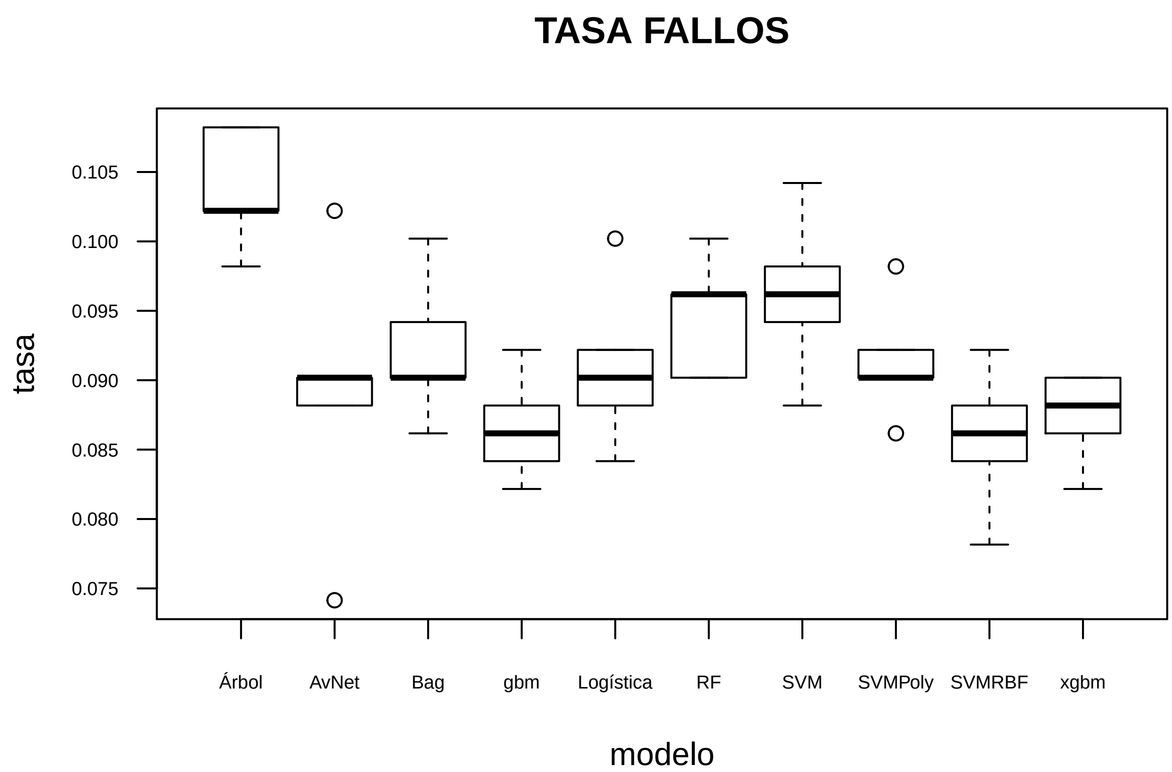
```
##   C sigma  Accuracy     Kappa AccuracySD  KappaSD
## 1 1   0.1 0.9142504 0.3902557 0.01775811 0.154883
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
## Setting levels: control = No, case = Yes
## Setting direction: controls < cases
```

```
svmrbf$modelo="SVMRBF"



union<-rbind(logi,avnet,arbol,bag,rf, gbm, xgbm, svm, svmp, svmrbf)

par(cex.axis=0.6, cex=1, las=1)
boxplot(data=union,tasa~modelo,main="TASA FALLOS")
```




```
boxplot(data=union,auc~modelo,main="AUC")
```